

Article

Multi-Objective Deployment Optimization of Unmanned Underwater Swarms in Realistic Ocean Environments

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Abstract

In marine environmental monitoring, target detection, identification and positioning, and other missions, the detection performance of unmanned underwater swarms directly depends on their deployment strategy. To address complex task scenarios requiring a balance between detection range, positioning accuracy, and connectivity, a multi-objective deployment optimization method is proposed in this paper. First, based on realistic underwater acoustic environment modeling using the Bellhop3D model, a collaborative detection model, positioning accuracy model, and network connectivity model for unmanned underwater platforms are established. These three models are integrated with weighted coefficients to construct the objective function, whose maximum value is sought to achieve optimal detection performance of the unmanned swarm. Second, an improved cuckoo search (ICS) algorithm is designed as the solution tool. The results demonstrate that the proposed deployment model achieves multi-objective balance and exhibits significant advantages over single-objective optimization models. Furthermore, the ICS algorithm obtains better solution quality than the compared intelligent optimization algorithms, providing an effective optimization tool for deployment in complex underwater acoustic environments.

Keywords: Bellhop3D model; deployment of unmanned underwater swarms; collaborative detection; cuckoo search algorithm

1. Introduction

With the rapid development of unmanned underwater technologies, underwater acoustic communication and detection techniques, and marine observation requirements, unmanned underwater swarms have become an important technical approach for marine environmental monitoring, target detection and recognition, positioning and tracking, and regional surveillance [1–3]. Compared with a single unmanned underwater platform, an unmanned underwater swarm can expand mission coverage and improve system robustness and detection reliability through multi-platform collaborative sensing, information interaction, and data fusion. However, the collaborative capability of such swarms strongly depends on the spatial deployment of the platforms. A rational deployment scheme not only determines the effective detection coverage within the target area, but also directly affects target positioning accuracy and inter-platform communication connectivity. Therefore, developing an optimized deployment method for unmanned underwater swarms in complex underwater environments is of great significance for improving the overall operational performance of underwater detection systems.



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The deployment of unmanned underwater swarms is a challenging problem. On the one hand, underwater acoustic propagation is affected by sound-speed profiles, seabed topography, seawater absorption, boundary reflection, and ambient noise, which leads to significant spatial non-uniformity in platform detection performance [4,5]. On the other hand, detection range, positioning accuracy, and communication connectivity are not mutually independent. Expanding detection coverage may result in an unfavorable geometric configuration for positioning, whereas improving positioning accuracy may restrict the spatial dispersion of platforms. Meanwhile, inter-platform connectivity is the basis for collaborative detection and information fusion. Some existing studies adopt idealized sensing models or simplified communication models, making it difficult to sufficiently describe the coupled constraints among multiple performance indicators in realistic marine environments. Therefore, it is necessary to develop a deployment optimization method that can jointly consider realistic acoustic propagation characteristics and multiple performance constraints.

Against this background, this study addresses three specific research questions. First, how can the spatially heterogeneous characteristics of underwater acoustic propagation in realistic marine environments be incorporated into the performance evaluation of unmanned underwater swarm deployment? Second, how can collaborative detection coverage, target positioning accuracy, and inter-platform connectivity be jointly modeled and balanced within a unified deployment framework? Third, how can the solution quality and convergence performance of the optimization process be improved for this high-dimensional, nonlinear, and non-convex deployment problem?

To address these questions, this paper proposes a multi-objective deployment optimization method for unmanned underwater swarms in realistic marine environments. The main contributions of this study are as follows:

1. Based on the Bellhop3D underwater acoustic propagation model, realistic marine environmental data are used to calculate propagation loss. A single-platform detection model that is more consistent with actual sea-area conditions is established, and a collaborative detection model based on connected components is further developed.
2. Three key performance indicators, namely effective detection coverage, effective positioning coverage, and platform connectivity rate, are jointly considered to construct a multi-objective optimization model for unmanned underwater swarm deployment, thereby achieving balanced optimization among detection range, positioning accuracy, and connectivity.
3. An improved cuckoo search algorithm is designed to solve the proposed multi-objective optimization model. Adaptive step-size Levy flight, an improved position update strategy, and a global-best-guided elimination and replacement rule are introduced to enhance the optimization accuracy and convergence performance of the algorithm.

The rest of this paper is organized as follows: Section 2 introduces the related work on underwater detection network deployment and intelligent optimization algorithms. Section 3 presents the mathematical models of unmanned underwater swarm deployment. Section 4 describes the improved cuckoo search algorithm used to solve the proposed multi-objective optimization problem. Section 5 reports the simulation experiments and analyzes the effectiveness of the proposed deployment model and algorithm. Section 6 summarizes this paper and discusses future research directions.

2. Related Work

The deployment of underwater detection networks is a fundamental problem in underwater sensor networks and collaborative detection by unmanned underwater swarms.

According to the optimization objectives, existing studies can generally be divided into detection coverage optimization, positioning accuracy improvement, connectivity maintenance, and multi-objective intelligent optimization [6]. Detection coverage optimization focuses on improving the effective coverage of the target area through rational node placement. Positioning accuracy improvement aims to optimize the geometric configuration of platforms so as to reduce target position estimation errors. Connectivity maintenance emphasizes the reliability of communication links among platforms, which supports collaborative detection and data fusion.

In terms of detection coverage optimization, Xia et al. [7] proposed an adaptive node deployment algorithm inspired by fish-swarm behavior to improve the detection coverage of underwater sensor networks. Song et al. [8] and Luo et al. [9] optimized node distribution based on the virtual force mechanism, thereby reducing detection blind areas. Huang et al. [10] proposed a deployment strategy based on detection fusion and adopted square and equilateral-triangle deployment schemes to achieve regional coverage. Aljughaiman [11] proposed a grid-based distributed deployment optimization algorithm to improve the coverage performance of underwater acoustic sensor networks. Kumar et al. [12] designed an underwater node deployment scheme based on intelligent optimization to improve regional coverage and network lifetime. These methods have achieved certain improvements in coverage optimization. However, some of them still rely on regular sensing ranges or idealized propagation assumptions, and the influence of complex marine environmental factors is not sufficiently considered.

In terms of positioning accuracy and connectivity optimization, Shakila et al. [13] proposed a positioning method based on a hybrid Spider Monkey Battle Royale (SMBR) algorithm, which improved the positioning accuracy of underwater sensor networks. Huang et al. [14] analyzed the effects of different topological structures on underwater positioning performance and indicated that a rational node topology can improve positioning performance. Su et al. [15] optimized node spatial distribution using Voronoi diagrams to enhance network connectivity. Priyadarshini et al. [16,17] improved coverage and connectivity during data transmission through energy prediction and failure recovery mechanisms. These studies demonstrate the importance of positioning accuracy and network connectivity for underwater collaborative detection. Nevertheless, most of them focus mainly on a single performance indicator and therefore cannot fully satisfy the joint requirements of detection, positioning, and communication.

Since practical underwater monitoring tasks usually need to satisfy multiple requirements, such as coverage, positioning, connectivity, and energy consumption, multi-objective deployment optimization has received increasing attention. Wang et al. [18] proposed an ant colony optimization-based self-deployment algorithm to maintain maximum coverage and network connectivity. Xia et al. [19] constructed an optimization model that maximizes coverage and reduces cost while guaranteeing full network connectivity. Liu et al. [20] developed a distributed node deployment method based on virtual forces, considering node density, residual energy, and movement effectiveness. Yi et al. [21] combined an improved greedy strategy with a depth-first search mechanism to decompose the global coverage problem into multiple local optimization problems. Yan et al. [22] improved coverage and energy efficiency through node depth adjustment. These studies have promoted the development of multi-objective deployment methods for underwater networks. However, most models are still mainly built around network coverage and communication connectivity, whereas the joint modeling of detection probability and positioning accuracy in realistic acoustic propagation environments remains insufficient.

In terms of optimization algorithms, genetic algorithms, particle swarm optimization, ant colony optimization, virtual force algorithms, and hybrid intelligent algorithms have

been widely used for underwater node deployment. Jin et al. [23] adopted a genetic algorithm for deployment optimization of underwater detection networks, but the convergence speed was relatively slow. Xu et al. [24] proposed a particle swarm optimization algorithm with network connectivity constraints and maintained connectivity during deployment through an adaptive position correction mechanism. Shen et al. [25] proposed a deployment algorithm combining virtual forces and particle swarm optimization, but its parameter tuning is relatively complicated. Overall, existing intelligent optimization algorithms are applicable to complex objective-function optimization. Representative underwater deployment studies are summarized in Table 1. As shown in Table 1, existing methods still have limitations in jointly modeling detection probability, positioning accuracy, and connectivity under realistic underwater acoustic environments. Therefore, this paper constructs a multi-objective deployment model based on realistic marine environment modeling and further designs an improved cuckoo search algorithm to improve solution quality and convergence performance.

Table 1. Comparison of representative underwater deployment studies.

Reference	Optimization Objective	Detection/ Coverage	Positioning	Connectivity	Environmental Realism	Algorithm
[7]	Maximize sensing coverage and adapt node density to event distribution	✓	×	×	×	Fish-swarm-inspired deployment algorithm
[8]	Improve three-dimensional sensing coverage and reduce coverage holes	✓	×	✓	×	Improved evidence-theory-based deployment algorithm
[9]	Maximize coverage in small-scale underwater sensor networks	✓	×	×	×	Virtual force algorithm
[10]	Maximize effective detection coverage using fewer sensor nodes	✓	×	✓	×	Detection-fusion-based regular topology deployment
[11]	Improve network coverage, connectivity, and energy efficiency	✓	×	✓	×	Distributed grid-based deployment algorithm
[12]	Maximize coverage and extend network lifetime	✓	×	×	×	Voronoi fuzzy c-means and swarm-intelligence-based optimization
[13]	Minimize target localization error and improve transmission performance	✓	✓	✓	×	Hybrid Spider Monkey Battle Royale algorithm
[14]	Improve localization accuracy through optimized network topology	✓	✓	×	✓	Topology configuration analysis
[15]	Improve three-dimensional coverage while maintaining connectivity	✓	×	✓	×	Voronoi-based depth adjustment algorithm
[16]	Maintain coverage and connectivity under node failures	✓	×	✓	×	Failure prediction, detection, and recovery algorithm
[17]	Improve coverage, connectivity, and energy efficiency in mobile networks	✓	×	✓	×	Energy-prediction-based deployment mechanism
[18]	Maximize coverage while maintaining network connectivity	✓	×	✓	×	Ant colony optimization algorithm
[19]	Maximize coverage and reduce deployment cost under full-connectivity constraints	✓	×	✓	×	Improved moth-flame optimization algorithm
[20]	Improve coverage, residual-energy balance, and movement efficiency	✓	×	×	✓	Distributed virtual force algorithm
[21]	Maximize target coverage and reduce deployment cost	✓	×	✓	×	Improved greedy strategy and depth-first search
[22]	Improve coverage and energy efficiency while maintaining network connectivity	✓	×	✓	×	Nonuniform depth-adjustment algorithm
[23]	Maximize underwater sensor-network coverage	✓	×	×	×	Genetic algorithm
[24]	Improve coverage and network performance under connectivity constraints	✓	×	✓	×	Connectivity-constrained particle swarm optimization
[25]	Improve coverage, routing efficiency, and data-collection performance	✓	×	✓	×	Virtual force–particle swarm optimization hybrid
This study	Jointly optimize effective detection coverage, effective positioning coverage, and platform connectivity	✓	✓	✓	✓	Improved cuckoo search algorithm

✓ indicates that the corresponding aspect is considered in the study, and × indicates that it is not considered.

3. Mathematical Model and Problem Formulation

To address the deployment problem of unmanned underwater platforms, an appropriate deployment model should first be established. In this study, the deployment model consists of a collaborative detection model, a positioning accuracy model, and a network connectivity model, which together provide the modeling foundation for the subsequent

multi-objective optimization algorithm. The main symbols involved in the deployment optimization model are summarized in Table 2.

Table 2. Main symbols used in the deployment optimization model.

Symbol	Definition	Unit
N	Number of unmanned underwater platforms	–
$X_i = [x_i, y_i]^T$	Position of platform i	km
(x_t, y_t)	Target or grid-point location	km
A_{sea}	Monitored two-dimensional sea area	km ²
P_D	Detection probability after collaborative fusion	–
P_F	Collaborative false alarm probability	–
P_{Dth}	Effective detection probability threshold	–
D_{cov}	Effective detection coverage rate	–
θ_i	Bearing angle from platform i to the target	rad
$\kappa(x_t, y_t)$	Positioning error at location (x_t, y_t)	km
κ_{th}	Effective positioning error threshold	km
P_{cov}	Effective positioning coverage rate	–
d_{ij}	Distance between platforms i and j	km
d_{max}	Maximum communication distance	km
C_{net}	Platform connectivity rate	–
F	Objective function of the deployment optimization model	–
$\omega_1, \omega_2, \omega_3$	Weights of detection coverage, positioning coverage, and connectivity	–

3.1. Collaborative Detection Model

Considering the characteristics of the underwater environment, the detection problem is modeled using a binary hypothesis testing framework [26], where H_1 denotes the presence of a target and H_0 denotes the absence of a target. Assuming that the observed signal at platform i is r_i , the hypotheses can be expressed as

$$\begin{aligned} H_0 : \quad & r_i = n_i, \\ H_1 : \quad & r_i = s_i + n_i, \end{aligned} \quad (1)$$

where s_i represents the target signal component and n_i denotes the noise component.

The observed signal is a random signal formed by the superposition of the useful signal and additive noise, and its statistical characteristics are largely determined by the statistical properties of the noise. According to the central limit theorem, under certain conditions, the sum of M mutually statistically independent discrete random signals n_k , denoted as $n = \sum_{k=1}^M n_k$, approximately follows a Gaussian distribution as $M \rightarrow \infty$. Therefore, when hypotheses H_0 and H_1 are true, the likelihood functions of the observed signal r_i can be expressed as

$$P(r_i | H_0) = \frac{1}{\sigma_n \sqrt{2\pi}} \exp \left[-\frac{(r_i - \mu_n)^2}{2\sigma_n^2} \right], \quad (2)$$

$$P(r_i | H_1) = \frac{1}{\sigma_{s+n} \sqrt{2\pi}} \exp \left[-\frac{(r_i - \mu_{s+n})^2}{2\sigma_{s+n}^2} \right], \quad (3)$$

where μ and σ denote the mean and standard deviation of the observed signal r_i , respectively, and the subscripts s and n represent the signal and noise components, respectively.

For an unmanned platform equipped with a passive sonar detection system, under long-range detection conditions, $\sigma_{s+n} \approx \sigma_n$. The output signal-to-noise ratio can thus be defined as $R_{SN} = (\mu_{s+n} - \mu_n)^2 / \sigma_n^2$. Assuming that the detection threshold is t_d , according to the Neyman–Pearson criterion, the false alarm probability P_F^i and detection probability P_D^i of a single platform can be obtained as follows [27]:

$$P_F^i = \int_{t_d}^{\infty} P(r_i | H_0) dr_i = 1 - \Phi\left(\frac{t_d - \mu_n}{\sigma_n}\right) = 1 - \Phi(\omega), \quad (4)$$

$$P_D^i = \int_{t_d}^{\infty} P(r_i | H_1) dr_i = 1 - \Phi\left(\frac{t_d - \mu_{s+n}}{\sigma_{s+n}}\right) = 1 - \Phi(\omega - \sqrt{R_{SN}}), \quad (5)$$

where $\Phi(\cdot)$ denotes the cumulative distribution function of the standard normal distribution. For a given false alarm probability P_F^i , the normalized threshold $\omega = (t_d - \mu_n)/\sigma_n$ can be obtained, and the corresponding detection probability P_D^i can then be derived.

As indicated by the passive sonar equation $DT = SL - TL - NL + G$, the transmission loss TL is one of the key parameters affecting the detection probability P_D^i . Owing to the complexity of the marine environment, simple models such as the Thorp model have relatively low computational complexity, but they cannot fully account for the combined effects of factors such as sound speed, seafloor topography, and depth on sound propagation. As a result, the errors in the computed transmission loss may be large. Therefore, the Bellhop3D model is adopted to realize the deployment of unmanned platforms in a two-dimensional sea area. The Bellhop3D model can perform underwater modeling by processing real ocean environmental data, thereby enabling the calculation of transmission loss at different distances from the sound source and significantly improving the reliability of detection performance evaluation. As shown in Figure 1, the transmission loss results calculated by the Thorp model and the Bellhop3D model show similar trends at short ranges. However, the Thorp model fails to capture the convergence zones formed at long ranges. In contrast, the Bellhop3D model can more accurately predict transmission loss under different environmental conditions, especially in complex deep-sea environments, where its accuracy is significantly higher than that of simple empirical models.

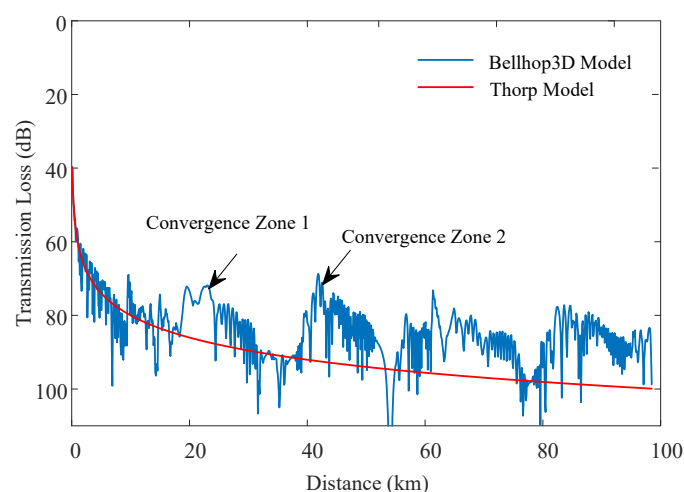


Figure 1. Comparison of transmission loss calculated by the Bellhop3D model and Thorp model.

This study focuses on the platform deployment problem in a two-dimensional plane. Therefore, the position of N platforms is assumed to be $X_i = [x_i, y_i]^T$, $i = 1, \dots, N$. The depth-first search (DFS) algorithm is adopted to identify connected components, and the specific procedure is as follows:

1. Initialize a Boolean vector visited of length N to record whether each platform has been visited.
2. Starting from any platform, perform recursive traversal using DFS.
3. During each traversal, if the distance between a platform that does not belong to the current connected component and the current platform does not exceed the maximum communication distance $d_{\max}$, and the platform has not been visited, the recursive traversal continues.

4. After the traversal is completed, k connected components are obtained, denoted as $C_c = \{C_c^1, C_c^2, \dots, C_c^k\}$, where C_c^j denotes the set of platforms in the j -th connected component, $j = 1, 2, \dots, k$.

As shown in Figure 2, the platforms are divided into several connected components according to the maximum communication distance $d_{\max}$. Platforms within the same connected component can exchange detection information and participate in collaborative detection, whereas isolated platforms are treated as single-platform components.

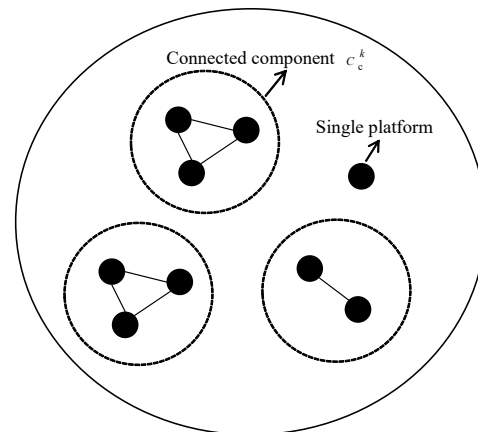


Figure 2. Four connected components identified by depth-first search (DFS). Each dashed circle denotes a connected component, and each black dot represents an underwater platform.

For the connected components composed of non-single platforms, collaborative detection is adopted. Assuming that the detection result of the i -th platform is u_i , which indicates whether a target is present, the optimal decision after fusion can be obtained according to the Neyman–Pearson criterion as

$$P(u_0 = 1|U) = \begin{cases} 1, & \Lambda(U) > \lambda, \\ \gamma, & \Lambda(U) = \lambda, \\ 0, & \Lambda(U) < \lambda, \end{cases} \quad (6)$$

where $U = (u_1, u_2, \dots, u_i)$ denotes the collaborative detection results, u_0 represents the final decision after fusion, and λ and γ denote the collaborative decision threshold and the randomization factor, respectively, with $\gamma \in (0, 1)$. In addition, $\Lambda(U) = P(U|H_1)/P(U|H_0)$ is the likelihood ratio. Therefore, the collaborative false alarm probability P_F and detection probability P_D of this connected component can be expressed as follows [28]:

$$P_F = \sum_{\Lambda(U) > \lambda} P(U|H_0) + \gamma \sum_{\Lambda(U) = \lambda} P(U|H_0), \quad (7)$$

$$P_D = \sum_{\Lambda(U) > \lambda} P(U|H_1) + \gamma \sum_{\Lambda(U) = \lambda} P(U|H_1). \quad (8)$$

Given the collaborative false alarm probability, the threshold λ and the randomization factor γ can be obtained using Equation (7), and the collaborative detection probability can then be determined.

Assuming that the k connected components are independent detection sources, the global detection probability at the target location $[x_t, y_t]^T$ is given by

$$P_D(x_t, y_t) = 1 - \prod_{j=1}^k (1 - P_D^j). \quad (9)$$

When the target area A_{sea} is divided into $m \times n$ grids, the effective detection coverage rate D_{cov} is defined as the ratio of the number of grids whose detection probability reaches the effective detection probability threshold $P_{D_{th}}$ to the total number of grids in the target area:

$$D_{cov} = \frac{1}{m \times n} \sum_{x_t=1}^m \sum_{y_t=1}^n \mathbb{I}(P_D(x_t, y_t) \geq P_{D_{th}}), \quad (10)$$

where $\mathbb{I}(\cdot)$ is the indicator function, which equals 1 when the condition is satisfied and 0 otherwise.

3.2. Positioning Accuracy Model

Suppose that there are N observation platforms in a two-dimensional monitoring area, and the position of the i -th platform is $X_i = [x_i, y_i]^T$. The target position to be estimated is $\mathbf{p}_t = [x_t, y_t]^T$. The true bearing angle of the target relative to platform i is

$$\theta_i = \text{atan2}(y_t - y_i, x_t - x_i). \quad (11)$$

The bearing-only observation model of platform i for the target is given by $z_i = \theta_i + v_i$, where v_i is zero-mean Gaussian noise, and the observation errors of different platforms are assumed to be mutually independent, namely $v_i \sim \mathcal{N}(0, \sigma_{\theta,i}^2)$. If all platforms are equipped with the same angle-measurement device, the standard deviation of the bearing measurement error is assumed to be identical for all platforms, i.e., $\sigma_{\theta,i} = \sigma_{\theta}$, $i = 1, \dots, N$. The coordinate differences and squared distance between the target and platform i are defined as $\Delta x_i = x_t - x_i$, $\Delta y_i = y_t - y_i$, and $r_i^2 = \Delta x_i^2 + \Delta y_i^2$.

When $r_i > 0$, the Jacobian row vector of the bearing angle with respect to the target position $\mathbf{p}_t$ is

$$\mathbf{H}_i = \frac{\partial \theta_i}{\partial \mathbf{p}_t} = \left[-\frac{\Delta y_i}{r_i^2}, \frac{\Delta x_i}{r_i^2} \right]. \quad (12)$$

If the distance between the target and platform i is smaller than a threshold $r_{\min}$, the platform observation is regarded as invalid and is not included in the valid observation set $\mathcal{V}$.

The weighted observation matrix is constructed by all valid platforms as

$$\mathbf{H}_w = \begin{bmatrix} \mathbf{H}_{i_1} / \sigma_{\theta,i_1} \\ \mathbf{H}_{i_2} / \sigma_{\theta,i_2} \\ \vdots \\ \mathbf{H}_{i_{|\mathcal{V}|}} / \sigma_{\theta,i_{|\mathcal{V}|}} \end{bmatrix}, \quad i_1, i_2, \dots, i_{|\mathcal{V}|} \in \mathcal{V}. \quad (13)$$

The Fisher information matrix of the target position can then be expressed as

$$\mathbf{J}(\mathbf{p}_t) = \mathbf{H}_w^T \mathbf{H}_w = \sum_{i \in \mathcal{V}} \frac{1}{\sigma_{\theta,i}^2} \mathbf{H}_i^T \mathbf{H}_i. \quad (14)$$

If the Fisher information matrix is full rank, the Cramér–Rao lower bound (CRLB) matrix of the target position estimation error is given by $\mathbf{C}_{\text{CRLB}} = \mathbf{J}^{-1}(\mathbf{p}_t)$. The positioning error is defined as the square root of the trace of the CRLB matrix, i.e., $\kappa(x_t, y_t) = \sqrt{\text{tr}(\mathbf{C}_{\text{CRLB}})}$.

The positioning error is regarded as infinite when the platforms and the target form a degenerate observation geometry, such as nearly collinear deployment, nearly parallel bearing lines, or overly clustered platform positions, which leads to insufficient angular diversity for two-dimensional localization.

The monitoring area is divided into $m \times n$ grids, and the target is assumed to be uniformly distributed over all grid points:

$$\Pr\{\mathbf{p}_t = (x_t, y_t)\} = \frac{1}{mn}. \quad (15)$$

The uniform assumption is only used to generate the global positioning performance statistic, and does not introduce additional prior information into the Fisher information matrix.

Given an error threshold κ_{th} , the effective positioning coverage rate is defined as

$$P_{cov} = \frac{1}{mn} \sum_{x_t=1}^m \sum_{y_t=1}^n I[\kappa(x_t, y_t) \leq \kappa_{th}], \quad (16)$$

where $I[\cdot]$ is the indicator function, which equals 1 if the condition is satisfied and 0 otherwise.

3.3. Connectivity Model

In an unmanned underwater swarm, connectivity constraints are a prerequisite for collaborative detection. Collaborative detection relies on information exchange among platforms, where each platform shares its detection data through communication links, and target positioning can be achieved only after data fusion. However, underwater acoustic communication is affected by geometric spreading, medium absorption, multipath effects, ocean noise, and other factors during propagation. As the communication distance increases, the propagation loss becomes larger and the communication link quality deteriorates. Therefore, underwater acoustic communication equipment usually has an effective communication range jointly determined by the transmit power, receiver sensitivity, operating frequency band, and environmental propagation loss. A link that satisfies the basic communication quality requirement can therefore be approximated by a distance-threshold constraint. Based on this consideration, this paper adopts a connectivity model based on the maximum communication distance. Constructing a binary adjacency relationship using the maximum communication distance can preserve a clear physical interpretation of the model while reducing the computational complexity of the optimization process. This enables the algorithm to efficiently determine whether platforms have information-exchange capability among a large number of candidate deployment schemes. According to the Euclidean distance $d_{ij} = \|X_i - X_j\|_2$ between platform i and platform j and the maximum communication distance $d_{\max}$, the adjacency matrix A_{ij} is defined as

$$A_{ij} = \begin{cases} 0, & i = j \text{ or } d_{ij} > d_{\max}, \\ 1, & i \neq j \text{ and } d_{ij} \leq d_{\max}. \end{cases} \quad (17)$$

To ensure platform connectivity, each platform is required to have at least two neighboring platforms. Therefore, the number of neighboring platforms of platform i , denoted as C_i , is expressed as

$$C_i = \sum_{\substack{j=1 \\ j \neq i}}^N A_{ij}. \quad (18)$$

The connectivity rate C_{net} represents the proportion of platforms satisfying the connectivity condition, with a value range of $[0, 1]$. Thus, the connectivity rate of the N platforms is defined as

$$C_{net} = \frac{1}{N} \sum_{i=1}^N \mathbb{I}(C_i \geq 2), \quad (19)$$

where $\mathbb{I}(\cdot)$ is the indicator function, which equals 1 when the condition is satisfied and 0 otherwise.

3.4. Problem Description

The deployment optimization problem is formulated under the following assumptions: First, the number and deployment depth of the unmanned underwater platforms remain fixed during the optimization process, and only their horizontal positions are optimized. Second, the marine environment is assumed to remain approximately stationary during a single optimization cycle, such that the precomputed underwater acoustic transmission-loss data remain valid throughout the optimization process. Third, the maximum communication distance $d_{\max}$ is determined by the communication capability of the equipment carried by the platforms and is treated as a known parameter during deployment optimization. Two platforms are considered capable of direct communication when the distance between them does not exceed $d_{\max}$. In the deployment problem, the optimization objective is to achieve optimal detection performance within a specified region under a fixed number of platforms. To obtain the optimal deployment scheme, the detection range, positioning accuracy, and connectivity are comprehensively considered to evaluate the deployment quality. Therefore, the multi-objective optimization problem is formulated as

$$\begin{aligned} \max \quad & F = \omega_1 D_{cov} + \omega_2 P_{cov} + \omega_3 C_{net} \\ \text{s.t.} \quad & \omega_1 + \omega_2 + \omega_3 = 1, \\ & \omega_i > 0, \quad i = 1, 2, 3, \\ & X = \{ \mathbf{X}_1, \mathbf{X}_2, \dots, \mathbf{X}_N \mid \mathbf{X}_i = [x_i, y_i]^T \} \subseteq A_{sea}. \end{aligned} \quad (20)$$

where ω_1 , ω_2 , and ω_3 are weighting coefficients that control the importance of the effective detection coverage rate, effective positioning coverage rate, and platform connectivity rate in the fitness function, respectively. X denotes the set of positions of all platforms, and A_{sea} denotes the monitored two-dimensional underwater region. Each platform must be located within the specified region to ensure the practical feasibility of the deployment scheme. It should be noted that the weight parameters are not fixed constants, but can be adjusted according to specific mission requirements. For example, when a mission emphasizes large-area early warning or surveillance, a larger weight can be assigned to the detection coverage term. When accurate target localization is more important, the weight of the positioning accuracy term can be increased. When communication reliability and collaborative information fusion are emphasized, the connectivity weight can be increased accordingly. In this study, the weighted-sum formulation is adopted to generate a single executable deployment scheme under different mission preferences.

4. Algorithm Design

The multi-objective optimization model constructed in this study is based on realistic underwater acoustic environmental modeling rather than the idealized simplified models commonly used in conventional studies. Meanwhile, the collaborative detection model introduces additional coupled constraints among detection coverage, positioning accuracy, and connectivity. Therefore, an optimization algorithm with good convergence performance and high search accuracy is required. In this paper, the Cuckoo Search (CS) algorithm, which involves simple parameter tuning, is adopted as the optimization tool and further improved to solve the proposed model.

4.1. Cuckoo Search Algorithm

Yang and Deb [29] proposed a heuristic optimization algorithm, namely the Cuckoo Search algorithm, which mimics the behavior of cuckoos laying eggs in the nests of other birds and searches for the global optimum through the Levy flight mechanism.

The algorithm updates the nest positions using the Levy flight mechanism and adjusts the search step size according to the current best solution. Assuming that the position of the i -th nest in the t -th generation is x_i^t , its position in the $(t + 1)$ -th generation is updated as

$$x_i^{t+1} = x_i^t + \alpha \oplus \text{Levy}(\beta)(x_{best} - x_i^t), \quad (21)$$

where x_{best} denotes the current best solution, α is the step-size factor, and $\text{Levy}(\beta)$ represents a random step size following the Levy distribution, which is given by

$$\text{Levy}(\beta) = \frac{\phi \times \zeta}{|\nu|^{1/\beta}}, \quad (22)$$

where ζ and ν follow standard normal distributions, and $\beta = 1.5$.

$$\phi = \left(\frac{\Gamma(1 + \beta) \times \sin\left(\pi \times \frac{\beta}{2}\right)}{\Gamma\left(\frac{1 + \beta}{2}\right) \times \beta \times 2^{\frac{\beta-1}{2}}}\right)^{1/\beta}. \quad (23)$$

Each host discovers alien eggs with a probability of P_a , and new solutions are generated through a biased random-walk strategy. The update is performed as follows:

$$x_i^{t+1} = x_j^t + \rho(x_j^t - x_k^t), \quad (24)$$

where ρ is a scaling factor, and x_j^t and x_k^t are two solutions randomly selected from the current population.

4.2. Improved Cuckoo Search Algorithm

In recent years, various improvement strategies have been proposed to address the limitations of the classical Cuckoo Search (CS) algorithm in terms of parameter adaptability, convergence accuracy, population initialization, and local search capability. Zheng et al. [30] enhanced the convergence speed, search accuracy, and ability to escape local optima of CS through adaptive parameter adjustment and a parallel communication strategy. Xiong et al. [31] dynamically configured the step-size factor based on a cloud model, thereby achieving adaptive adjustment of the search control parameter. Min et al. [32] combined chaotic mapping, random migration, beetle antennae search guidance, and a sine-cosine local exploitation strategy to improve the search performance of CS in robot path planning. Sun [33] proposed an improved cuckoo search algorithm based on a sharing mechanism, in which population initialization and information sharing among individuals were enhanced to improve the search capability and convergence performance of CS. Villanueva et al. [34] proposed an enhanced cuckoo search algorithm (ECSA), which introduced Sobol-sequence-based population initialization and cosine annealing with warm restarts to improve population diversity and dynamically adjust the discovery probability and step-size parameters. These recent studies indicate that improvements to CS algorithms have mainly focused on adaptive parameter control, high-quality population initialization, information-sharing mechanisms, hybrid search strategies, and the balance between global exploration and local exploitation. Since the objective function in this study requires repeated grid-based evaluations of detection coverage, positioning accuracy, and network connectivity, the optimization process should emphasize global exploration in the early

iterations and enhance local exploitation in the later iterations. Therefore, inspired by the above studies and based on the classical CS algorithm, this paper designs an improved cuckoo search algorithm (ICS) to improve the adaptability of CS to the proposed unmanned underwater platform deployment optimization problem.

According to the study on the Cuckoo Search algorithm in [29], a step-size factor of $\alpha = 1$ can generally achieve good performance in most optimization problems. However, in practical applications, a fixed step-size factor α may lead to a slow convergence rate or insufficient search accuracy. Therefore, an adaptive step-size mechanism is introduced in this study, and the step-size factor α is dynamically adjusted to obtain the global optimal solution:

$$\alpha = \alpha_0 \times \exp\left(-\frac{t_i}{t_{\max}}\right), \quad (25)$$

where $\alpha_0 = 1$ is the initial step-size factor, t_i is the current iteration number, and $t_{\max}$ is the maximum number of iterations. The step-size factor decreases exponentially with the iteration process. When $t_i \in [0, \frac{1}{3}t_{\max}]$, the step size remains above 0.7, which is beneficial for global exploration. When $t_i \in (\frac{1}{3}t_{\max}, \frac{2}{3}t_{\max}]$, the step size ranges from 0.5 to 0.7, achieving a balance between global exploration and local exploitation. When $t_i \in [\frac{2}{3}t_{\max}, t_{\max}]$, the step size decreases below 0.5, and the search process gradually shifts to local exploitation.

The adaptive step-size factor is used to balance global exploration and local exploitation. In the early iterations, a larger step size helps the algorithm search within a wider deployment space and reduces the risk of premature convergence. In the later iterations, a smaller step size helps refine platform positions around promising solutions, thereby improving local search accuracy.

In the standard Cuckoo Search algorithm, the position of each individual is updated according to Equation (21). In this study, the position update strategy is improved by replacing the original position vector difference with a random vector. The modified position update equation is expressed as

$$\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \alpha \oplus \text{Levy}(\beta) \cdot \mathbf{r}, \quad (26)$$

where $\mathbf{r}$ is a $2N$ -dimensional random vector with each component randomly generated within $(-1, 1)$. It controls the movement direction and amplitude of each coordinate component in the $2N$ -dimensional search space.

To improve the search efficiency of the algorithm, the nest replacement formula in Equation (24) is also modified. When a random number is smaller than the discovery probability P_a , the new solution is generated using a biased search strategy guided by the global optimal solution:

$$\mathbf{x}_i^{t+1} = \mathbf{x}_{\text{best}}^t + \delta \cdot v(\mathbf{x}_{\text{best}}^t - \mathbf{x}_i^t), \quad (27)$$

where $\mathbf{x}_{\text{best}}^t$ denotes the current global optimal solution, v is a random number within $(0, 1)$, and δ is the step-size control parameter.

The random-vector-based Levy update in Equation (26) increases search diversity by perturbing different platform coordinates independently in the $2N$ -dimensional search space. The global-best-guided replacement strategy in Equation (27) further enhances exploitation around the best solution found so far. Compared with purely random replacement, this strategy is more likely to generate high-quality neighboring solutions, thereby improving convergence speed and search quality.

Based on the above discussion, the complete ICS algorithm is summarized in Algorithm 1.

Algorithm 1 ICS

Input: Maximum number of iterations T ; population size K ; discovery probability P_a ; initial step-size factor $\alpha_0 = 1$; Levy-flight exponent β ; global-best-guided step-size parameter δ ; objective function F ; search space A_{sea} .

Output: Global optimal position x_{best} .

```

1:  $t \leftarrow 0$ 
2: Initialize the population positions  $X_0 = (x_1^0, x_2^0, \dots, x_K^0)$ .
3: Calculate the objective function value of each individual:  $F_i = F(x_i)$ ,  $i = 1, 2, \dots, K$ .
4: Determine the optimal position  $x_{best}^0$  and the best objective function value  $F_{max}$ .
5: while  $t < T$  do
6:   for  $i = 1$  to  $K$  do
7:     Calculate the step-size factor  $\alpha$  according to Equation (25).
8:     Generate a new position  $x_i^{t+1}$  using the improved Levy flight strategy in Equation (26).
9:     if  $F(x_i^{t+1}) > F(x_i^t)$  then
10:      Replace the current position with the new position:  $x_i^t \leftarrow x_i^{t+1}$ .
11:     end if
12:   end for
13:   for  $i = 1$  to  $K$  do
14:     if  $\text{rand} < P_a$  then
15:       Replace  $x_i^t$  with  $x_i^{t+1}$  using the biased random walk strategy in Equation (27).
16:     end if
17:   end for
18:   Update the global optimal position  $x_{best}^t$ .
19:    $t \leftarrow t + 1$ .
20: end while
21: return  $x_{best}$ .

```

5. Simulation and Performance Evaluation

5.1. Model Validation Analysis

5.1.1. Analysis of the Collaborative Detection Model

A sea area of $500 \text{ km} \times 500 \text{ km}$ in the South China Sea was selected as the simulation scenario. This region is characterized by complex seabed topography and contains various marine environmental features, including shallow-water areas, continental shelf regions, and deep-sea areas. The environmental data were obtained from the World Ocean Atlas 2023 (WOA23) monthly mean temperature–salinity–depth dataset with a spatial resolution of $0.25^\circ \times 0.25^\circ$ and the General Bathymetric Chart of the Oceans (GEBCO) bathymetric dataset with a resolution of 15 arcsec.

Three platforms were deployed at a water depth of 1000 m and arranged in an equilateral-triangle topology. The platform locations were set to (500, 850) km, (500, 900) km, and (550, 875) km, respectively. The simulation area was discretized into square grids with a grid resolution of $1 \text{ km} \times 1 \text{ km}$. In the simulation, the effective detection threshold was set to 0.8, the source level was set to 165 dB, the ambient noise level was 70 dB, the receiver system gain was set to 30 dB, the single-platform false alarm probability was $P_f = 0.001$, and the collaborative false alarm probability was $P_F = 0.01$. The detection results over 12 months were obtained under both the collaborative detection mode and the non-collaborative detection mode, as shown in Figures 3 and 4.

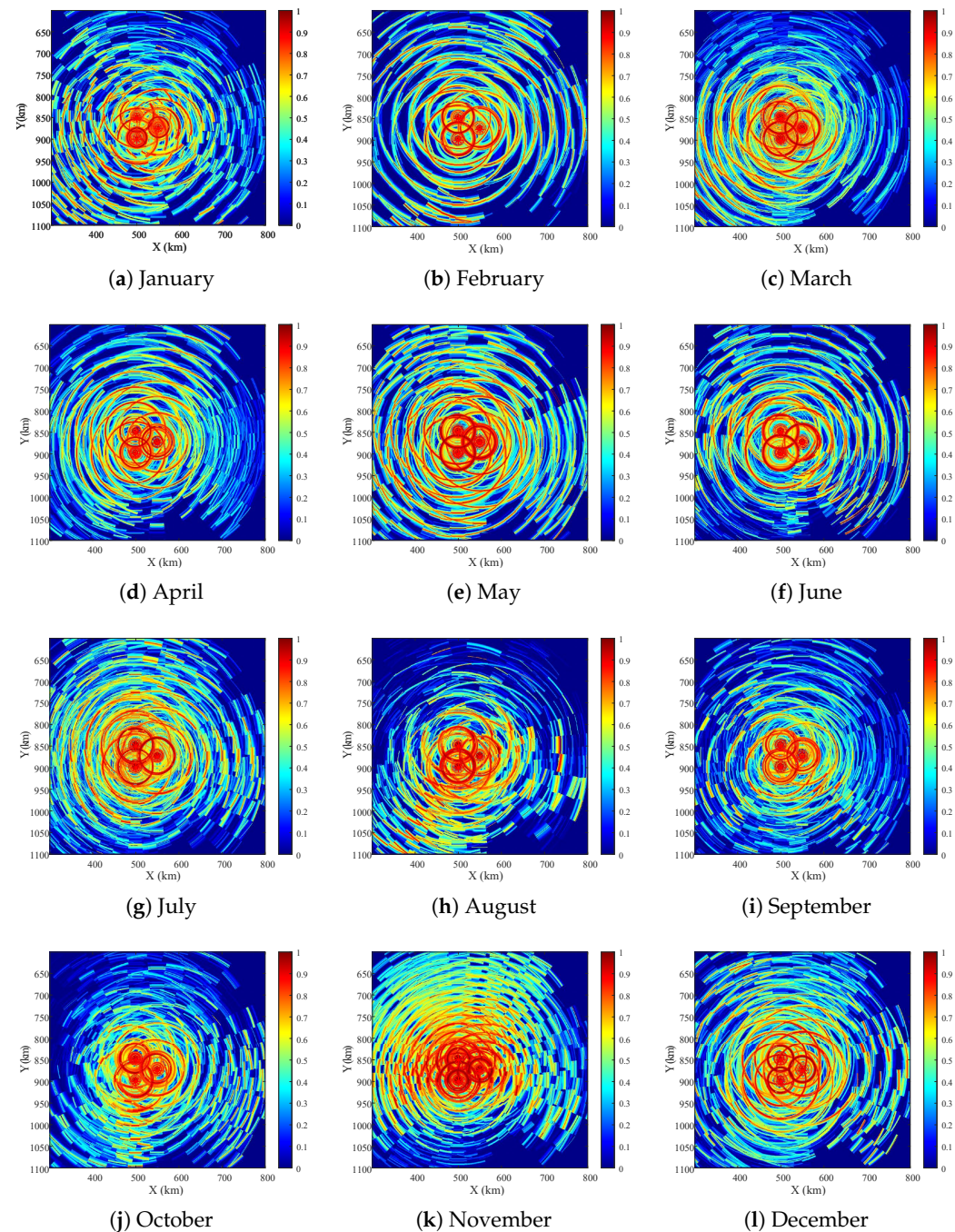


Figure 3. Monthly non-collaborative detection results of unmanned platforms from January to December. The color bar represents the detection probability P_D , and the red stars indicate the platform locations.

As shown in Figures 3 and 4, the detection capability of each platform exhibits significant directional variations. This phenomenon is mainly attributed to the influence of surrounding topography, sound-speed structure, and other environmental factors. In the collaborative detection mode, information from different platforms is integrated through data fusion, which effectively reduces detection blind zones and expands the high-probability detection coverage. In contrast, under the non-collaborative detection mode, the platforms do not exchange information, which limits the overall detection performance and reflects the spatial limitations of single-platform detection.

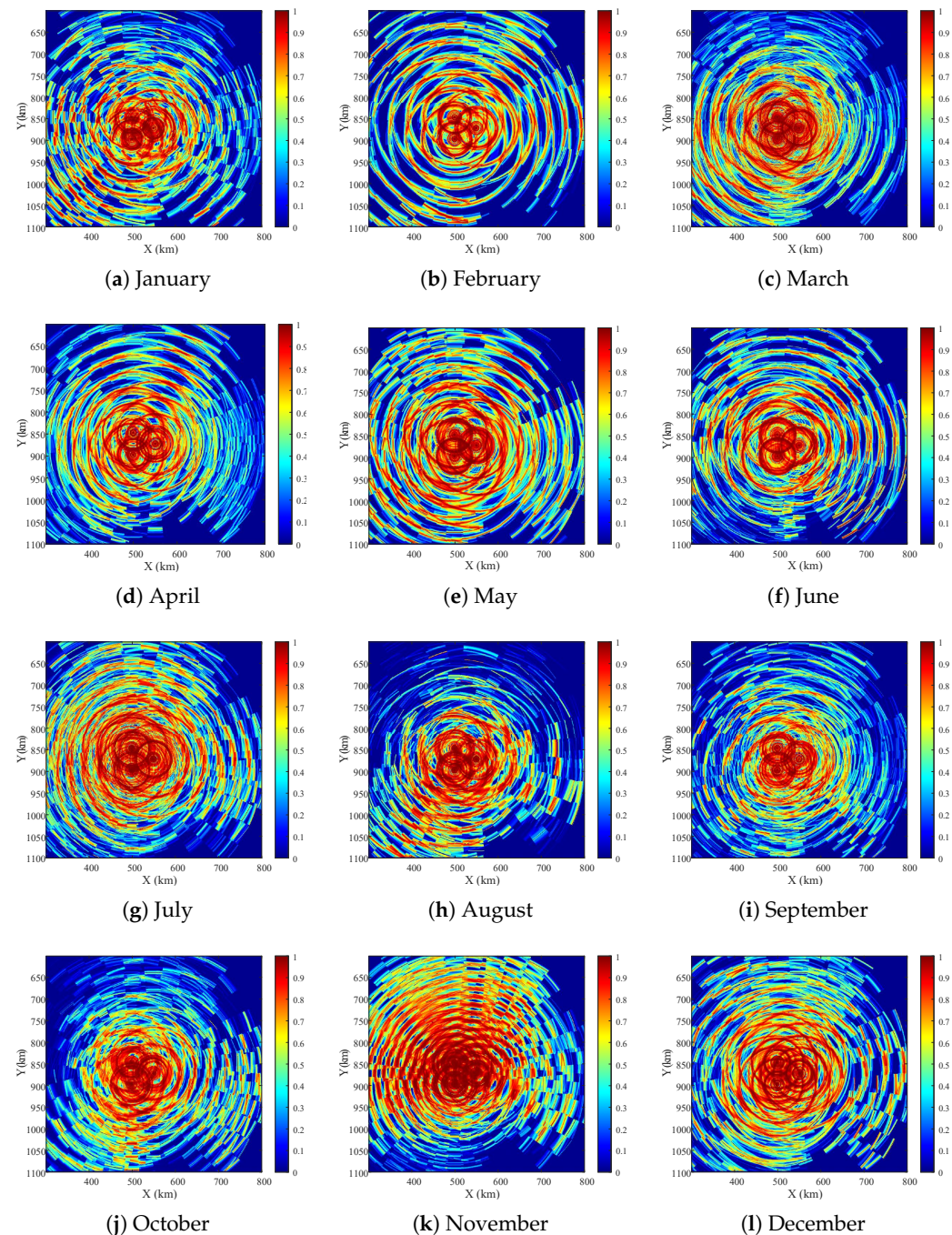


Figure 4. Monthly collaborative detection results of unmanned platforms from January to December. The color bar represents the collaborative detection probability, and the red stars indicate the platform locations.

As shown in Table 3, the effective detection coverage rates of both detection modes exhibit evident monthly fluctuations. This seasonal variability is mainly caused by the dynamic variation in marine environmental parameters. On the one hand, seasonal changes in the temperature–salinity structure of seawater lead to differences in the sound-speed profile, thereby affecting acoustic propagation paths and detection ranges. On the other hand, seasonal variations in sea-state conditions, such as wind-wave intensity and current velocity, as well as ambient noise levels, also have a significant influence on underwater detection performance. Compared with the non-collaborative detection mode, the collaborative detection mode demonstrates a clear advantage throughout the year. The results show that

its effective detection coverage rate is approximately two to three times that of the non-collaborative mode. Moreover, the collaborative mode maintains relatively stable detection performance even under unfavorable environmental conditions, fully demonstrating the important role of the collaborative mechanism in enhancing system robustness.

Table 3. Comparison of effective detection coverage rates under the two detection modes from January to December.

Detection Mode	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sep.	Oct.	Nov.	Dec.
Non-collaborative detection	4.08%	4.55%	4.31%	3.98%	7.80%	4.79%	4.92%	4.67%	2.29%	3.61%	8.46%	5.82%
Collaborative detection	9.81%	9.01%	11.28%	8.83%	15.34%	10.98%	15.24%	11.26%	7.28%	9.49%	22.31%	14.28%

5.1.2. Analysis of the Multi-Objective Optimization Model

A 200 km $\times$ 200 km sea area in the western Pacific Ocean was selected for the simulation experiment of underwater platform deployment. The deployment region was discretized into square grids with a grid resolution of 1 km $\times$ 1 km. In practical engineering scenarios, the manufacturing and deployment costs of unmanned underwater platforms are relatively high, and the number of available platforms is therefore usually strictly limited. Accordingly, six platforms were considered in this simulation, with a uniform deployment depth of 1000 m. Two types of environmental data were used: the WOA23 annual mean temperature–salinity–depth dataset with a spatial resolution of $0.25^\circ \times 0.25^\circ$ and the GEBCO bathymetric dataset with a spatial resolution of 15 arcsec. Based on the temperature, salinity, and depth data provided by WOA23, the sound speed at different horizontal positions and depths was calculated using an empirical sound-speed formula, thereby constructing the corresponding sound-speed profiles. The Bellhop3D geometric Gaussian beam model was then used to precompute the transmission loss fields for different platform positions, and the resulting data were stored in a transmission-loss database. During the optimization process, Bellhop3D was not executed repeatedly. Instead, the corresponding transmission loss was retrieved from the precomputed database according to the distance and bearing between each platform and target grid point.

The source level and deployment depth settings were selected according to underwater acoustic equipment capabilities, typical platform operating depths, and scenario-specific environmental constraints. The simulation parameters were configured as follows: the effective detection threshold was set to 0.8, the effective positioning error threshold was set to 5 km, the standard deviation of the bearing-measurement error was set to $\sigma_\theta = 5^\circ$, and the maximum effective communication distance was set to 100 km. The single-platform false alarm probability was set to $P_f = 0.001$, and the collaborative detection false alarm probability was set to $P_F = 0.01$. The source level, ambient noise level, and receiver system gain were set to 125 dB, 70 dB, and 30 dB, respectively. For the algorithm configuration, the population size was set to 8, and the maximum number of iterations was set to 200. All experiments were conducted on a computer equipped with a 13th Gen Intel(R) Core(TM) i5-13500 processor operating at 2.50 GHz and 16 GB of RAM.

According to the data in Table 4, different combinations of weight parameters produce clear trade-offs among the system performance metrics. When $\omega_1 = 0.80$, which emphasizes the optimization of detection coverage, the optimized deployment achieves the highest effective detection coverage rate among all the tested combinations, reaching 45.08%, while the effective positioning coverage rate is 40.13%. When $\omega_2 = 0.80$, which focuses on improving positioning performance, the optimized deployment obtains the highest effective positioning coverage rate of 49.60%, whereas the effective detection coverage rate decreases to 40.25%. When ω_2 is fixed at 0.30, increasing ω_1 from 0.40 to 0.60 while decreasing ω_3 from 0.30 to 0.10 increases the effective detection coverage rate from 41.45%

to 44.24%, but decreases the effective positioning coverage rate from 47.99% to 46.17%. Combined with the results shown in Figures 5 and 6, this phenomenon mainly results from the inherent trade-off between detection coverage optimization and positioning accuracy improvement. Improving the detection coverage generally requires the platforms to be distributed over a wider area, which may deteriorate their positioning geometry. Conversely, improving positioning accuracy requires the favorable geometric configuration of the platforms, which may restrict their spatial dispersion and consequently reduce the detection coverage. The connectivity rate remains at 100% for all weight combinations, indicating that all optimized deployment schemes satisfy the prescribed connectivity condition. This is mainly because platforms with insufficient communication links cannot effectively participate in collaborative detection and information fusion, thereby reducing the overall objective-function value. When a relatively balanced weight allocation is adopted, namely $\omega_1 = 0.40$, $\omega_2 = 0.30$, and $\omega_3 = 0.30$, the optimized deployment achieves an effective detection coverage rate of 41.45%, an effective positioning coverage rate of 47.99%, and a connectivity rate of 100%, providing a balanced compromise among the three performance objectives. Therefore, in the platform deployment problem, detection coverage and positioning accuracy exhibit an evident trade-off, while communication connectivity acts as an important constraint for collaborative operation. Considering only a single performance objective may degrade the other performance metrics, whereas the proposed multi-objective optimization model can achieve balanced overall performance by adjusting the weight parameters according to different mission requirements.

Table 4. Influence of different weight-parameter combinations.

Weight Parameters			Effective Detection Coverage Rate	Effective Positioning Coverage Rate	Connectivity Rate	Average Time per Iteration
ω_1	ω_2	ω_3				
0.80	0.10	0.10	45.08%	40.13%	100%	29.02 s
0.10	0.80	0.10	40.25%	49.60%	100%	35.48 s
0.10	0.10	0.80	41.70%	48.20%	100%	29.92 s
0.40	0.30	0.30	41.45%	47.99%	100%	29.75 s
0.50	0.30	0.20	43.90%	46.92%	100%	32.31 s
0.60	0.30	0.10	44.24%	46.17%	100%	30.23 s

To analyze the influence of the maximum communication distance assumption on the collaborative detection model, four communication-distance constraints, namely 50 km, 75 km, 100 km, and 125 km, were considered under the weight-parameter setting of $\omega_1 = 0.5$, $\omega_2 = 0.3$, and $\omega_3 = 0.2$. Deployment optimization was then performed under the same experimental conditions. The results in Table 5 show that the maximum communication distance affects the collaborative topology formed among platforms, thereby changing the balance among detection coverage, positioning coverage, and overall fitness. When the maximum communication distance is 50 km, although the optimized result still satisfies the connectivity constraint, the positioning coverage rate is relatively low, indicating that a stricter communication-distance constraint restricts the feasible collaborative deployment geometry of the platforms. When the communication distance increases to 75 km, the highest overall fitness is achieved, indicating that appropriately relaxing the communication constraint can improve the overall deployment performance. However, as the communication distance further increases, the performance does not show a monotonic improvement. This is because the final optimization result is not only affected by the communication topology constraint, but is also jointly influenced by detection coverage, positioning geometry, and realistic acoustic propagation conditions. It should be noted that the maximum communication distance in this paper mainly serves as a feasibility constraint for collaborative detection data exchange and is used to determine whether plat-

forms have basic communication capability. In practical applications, this parameter should be specifically set according to the performance of underwater acoustic communication equipment, mission requirements, and ocean environmental conditions.

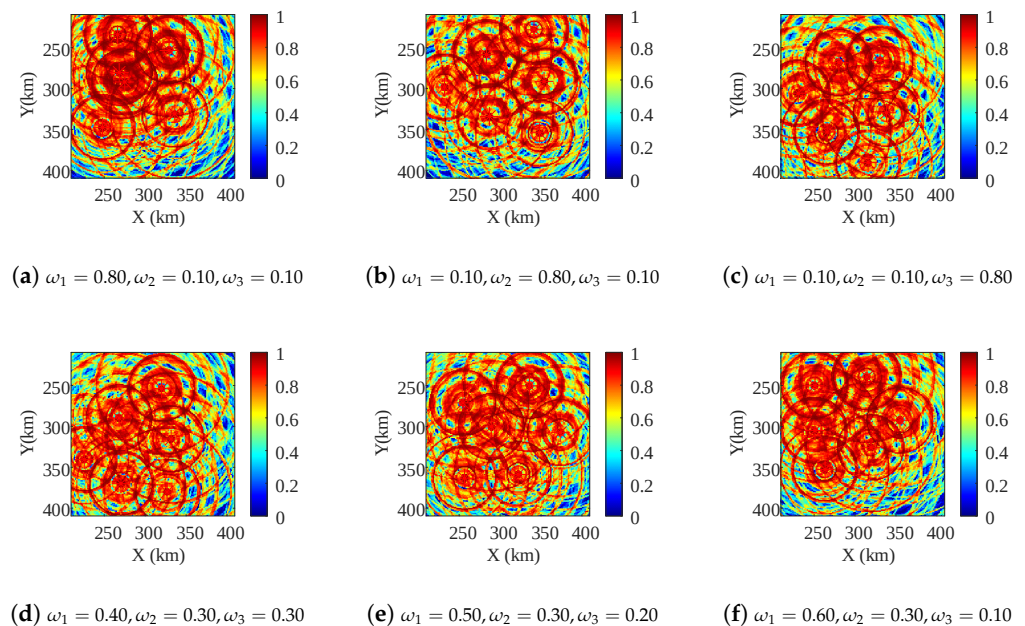


Figure 5. Optimized collaborative detection results under different combinations of weight parameters. The color bar represents the collaborative detection probability P_D , and the red stars indicate the optimized platform locations.

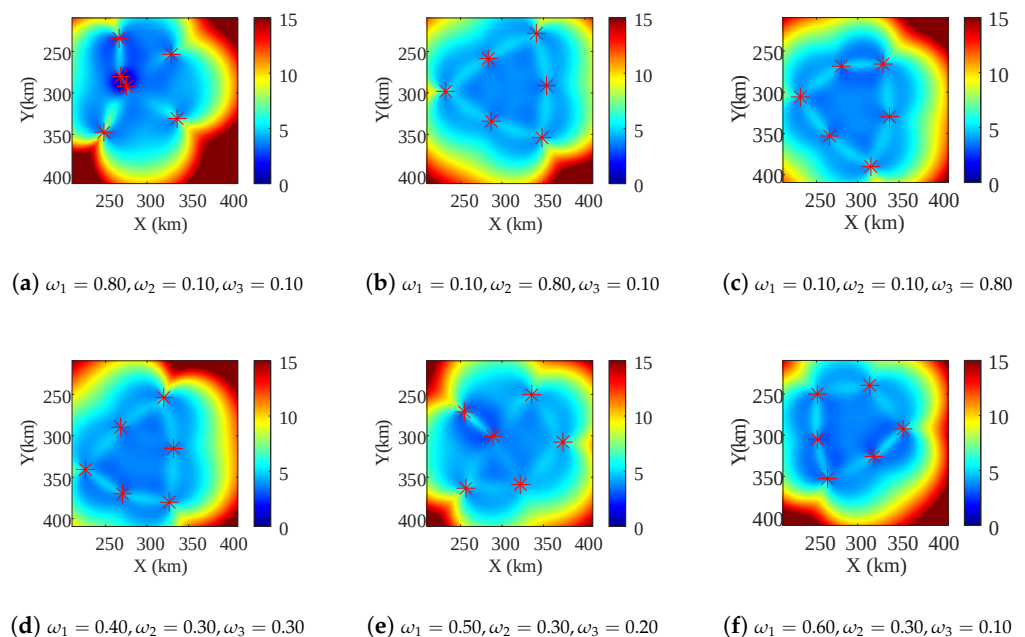


Figure 6. Optimized positioning accuracy results under different combinations of weight parameters. The color bar represents the positioning error $\kappa(x_t, y_t)$ in kilometers, and the red stars indicate the optimized platform locations.

The average computational time per iteration was further recorded for each group of experiments. The results in Tables 4 and 5 show that, under the current experimental settings, the average computational time per iteration is approximately 30 s. This computational cost mainly comes from the objective-function evaluation process. Instead of using an idealized circular detection radius or a simplified propagation-loss model, this study

introduces realistic ocean environmental data and evaluates detection coverage, positioning accuracy, and network connectivity point by point over the grid. Therefore, compared with idealized deployment models, the proposed method requires more environment-related computations in each iteration. However, this is a necessary cost for improving the physical rationality and reliability of the deployment results.

Table 5. Comparison of optimization results under different maximum communication distances.

Maximum Communication Distance	Fitness	Effective Detection Coverage Rate	Effective Positioning Coverage Rate	Connectivity Rate	Average Time per Iteration
50 km	53.11%	43.97%	37.09%	100%	30.16 s
75 km	56.29%	44.99%	46.00%	100%	30.80 s
100 km	56.03%	43.90%	46.92%	100%	32.31 s
125 km	55.27%	43.54%	44.98%	100%	28.96 s

5.2. Algorithm Performance Verification

To evaluate the convergence performance, solution quality, and stability of the proposed improved cuckoo search (ICS) algorithm, it was compared with the improved cuckoo search algorithm based on a sharing mechanism (ICSABOSM) reported in [33], the enhanced cuckoo search algorithm (ECSA) reported in [34], the virtual-force-directed particle swarm optimization (VF-PSO) algorithm reported in [25], and the standard cuckoo search (CS) algorithm [29]. A 300 km × 300 km sea area in the western Pacific Ocean was selected as the deployment region. The deployment region was discretized into square grids with a grid resolution of 1 km × 1 km. The number of unmanned underwater platforms was set to 15, and the deployment depth was fixed at 1000 m. The environmental data were obtained from the WOA23 annual mean temperature–salinity–depth dataset with a spatial resolution of 0.25° × 0.25° and the GEBCO bathymetric dataset with a spatial resolution of 15 arcsec. The effective detection probability threshold, effective positioning error threshold, standard deviation of the bearing-measurement error, and maximum communication distance were set to 0.8, 5 km, $\sigma_\theta = 5^\circ$, and 100 km, respectively. The single-platform false alarm probability and collaborative false alarm probability were set to $P_f = 0.001$ and $P_F = 0.01$, respectively, while the source level, ambient noise level, and receiver system gain were set to 125 dB, 70 dB, and 30 dB, respectively. The objective-function weights were set to $\omega_1 = 0.50$, $\omega_2 = 0.30$, and $\omega_3 = 0.20$. To ensure a fair comparison, all algorithms used the same population size of 10, maximum number of iterations of 200, initialization range, boundary-handling strategy, and objective-function evaluation procedure. For the standard CS algorithm, the discovery probability, step-size factor, and Levy-flight exponent were set to $P_a = 0.25$, $\alpha = 1$, and $\beta = 1.5$, respectively. For the proposed ICS algorithm, the discovery probability, initial step-size factor, Levy-flight exponent, and global-best-guided step-size control parameter were set to $P_a = 0.25$, $\alpha_0 = 1$, $\beta = 1.5$, and $\delta = 0.5$, respectively, with the step-size factor adaptively updated according to Equation (25). Except for the population size and maximum number of iterations, which were unified for a fair comparison, the algorithm-specific parameters of ICSABOSM [33], ECSA [34], and VF-PSO [25] were set according to their original publications, and no additional problem-specific parameter tuning was performed for the comparison algorithms. Considering the stochastic nature of the algorithms, each algorithm was independently executed 10 times using different random seeds. At each iteration, the best-so-far fitness values obtained from the 10 independent runs were averaged to generate the convergence curves. The final fitness value, effective detection coverage rate, effective positioning coverage rate, and connectivity rate were reported as the mean and standard deviation (SD) of the 10 independent runs.

As shown in Figures 7 and 8, the mean best-so-far convergence curves of the five algorithms exhibit different convergence characteristics. The standard CS algorithm con-

verges relatively slowly and approaches a stable solution after approximately 150 iterations, whereas the algorithms in [25,33,34], as well as the proposed ICS algorithm, generally reach stable solutions within approximately 80–120 iterations. Among them, the proposed ICS algorithm maintains a relatively fast convergence rate and obtains the highest final mean fitness value. As presented in Table 6, the proposed ICS algorithm achieves a mean fitness value of $76.19\% \pm 0.18\%$, a mean effective detection coverage rate of $66.53\% \pm 0.28\%$, and a mean effective positioning coverage rate of $76.41\% \pm 0.33\%$. Compared with the standard CS algorithm, the proposed ICS improves the mean fitness value from 74.90% to 76.19%, the effective detection coverage rate from 65.49% to 66.53%, and the effective positioning coverage rate from 73.84% to 76.41%. These results indicate that the adaptive step-size mechanism and the global-best-guided update strategy effectively improve both the solution quality and convergence stability. Compared with the recent improved cuckoo-search-based algorithms in [33,34], the proposed ICS also shows competitive or superior performance. Specifically, ICS obtains the highest mean fitness value among all compared algorithms. For the effective detection coverage rate, ICS achieves the same mean value as the algorithm in [34], while outperforming the algorithms in [25,33], and the standard CS algorithm. For the effective positioning coverage rate, ICS achieves the best result, indicating that it is particularly effective in improving the geometric deployment quality related to positioning accuracy. In addition, the standard deviations of the results obtained by ICS are relatively small, suggesting that the proposed algorithm can provide stable and robust optimization results over the 10 independent runs. All algorithms achieve a connectivity rate of 100.00%, indicating that all platforms in the resulting deployment schemes satisfy the prescribed local connectivity condition of having at least two neighboring platforms. Therefore, in this experiment, the connectivity term mainly acts as a feasibility constraint, while the performance differences among the algorithms are primarily reflected in the fitness value, effective detection coverage rate, and effective positioning coverage rate.

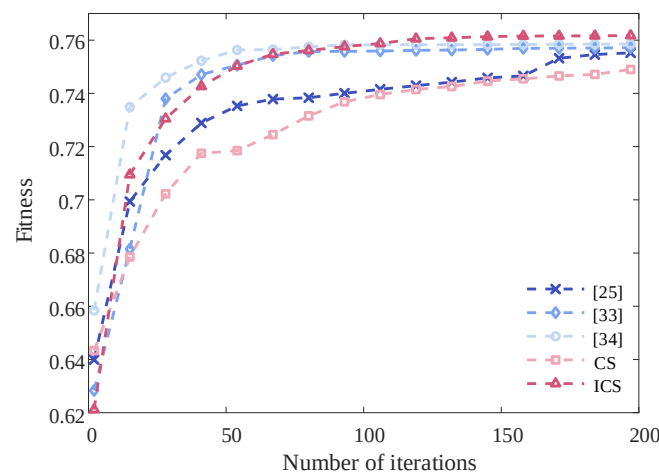


Figure 7. Mean best-so-far fitness convergence curves of different algorithms over 200 iterations, averaged over 10 independent runs.

Table 6. Comparison of optimization results obtained by different algorithms over 10 independent runs.

Algorithm	Fitness Mean $\pm$ SD (%)	Effective Detection Coverage Rate Mean $\pm$ SD (%)	Effective Positioning Coverage Rate Mean $\pm$ SD (%)	Connectivity Rate Mean $\pm$ SD (%)
[25]	75.52 ± 0.36	66.01 ± 0.52	75.07 ± 0.68	100.00 ± 0.00
[33]	75.71 ± 0.28	65.96 ± 0.34	75.77 ± 0.38	100.00 ± 0.00
[34]	75.85 ± 0.18	66.53 ± 0.25	75.29 ± 0.36	100.00 ± 0.00
CS	74.90 ± 0.44	65.49 ± 0.61	73.84 ± 0.75	100.00 ± 0.00
ICS	76.19 ± 0.18	66.53 ± 0.28	76.41 ± 0.33	100.00 ± 0.00

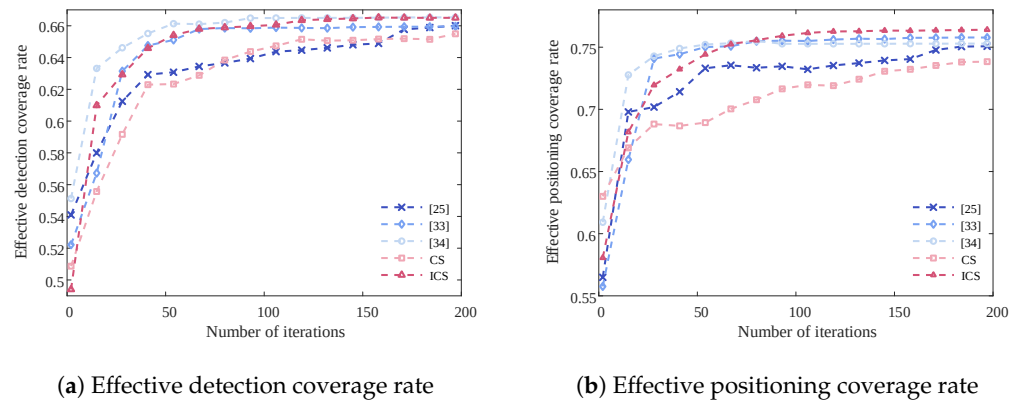


Figure 8. Mean convergence curves of different algorithms over 200 iterations, averaged over 10 independent runs.

6. Conclusions

This study proposed an unmanned platform deployment method for realistic underwater environments, with the maximization of detection performance as the core objective. The complex underwater platform deployment problem was transformed into a multi-objective optimization problem. By reasonably modeling detection coverage, positioning accuracy, and platform connectivity, three performance evaluation metrics were defined, namely the effective detection coverage rate, effective positioning coverage rate, and connectivity rate. The ICS algorithm was then adopted to achieve a balanced improvement of these three metrics. The results demonstrate that: (1) The collaborative detection model reduces detection blind zones through information fusion among platforms, thereby improving the effective detection coverage rate; (2) The multi-objective optimization model comprehensively considers multiple factors and ensures the overall performance optimization of the underwater platform cluster; (3) Compared with other intelligent optimization algorithms, the ICS algorithm exhibits advantages in convergence performance and solution quality.

Future work will further consider complex factors in practical engineering scenarios, including incorporating target motion characteristics and Doppler effects into the optimization model to improve the specificity of the detection scheme, as well as introducing platform self-noise and energy-constrained conditions to construct a dynamic redeployment strategy and enhance the adaptability of the detection scheme. In addition, considering that the computational burden may increase significantly with the number of platforms, the deployment area, and the grid resolution, the scalability of the proposed method for large-scale unmanned underwater swarm deployment will be further investigated. Future research will also explore the integration of the proposed ICS algorithm with other intelligent optimization algorithms to improve computational efficiency and further enhance its applicability to large-scale deployment optimization problems.

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